Volume 12 • Number 2 • 2009
VALUE IN HEALTH

Does Attribute Framing in Discrete Choice Experiments Influence Willingness to Pay? Results from a Discrete Choice Experiment in Screening for Colorectal Cancer

Kirsten Howard, BSc(Hons I), MAppSc(Biopharm), MPH, MHealthEcon, PhD,
Glenn Salkeld, BBus, GradDipHealthEcon, MPH, PhD

Screening and Test Evaluation Program (STEP), School of Public Health, University of Sydney, Sydney, NSW, Australia

ABSTRACT

Objective: Recent reviews of discrete choice methodology identified methodological issues warranting further exploration, including the issue of "framing." The objective of this study was to conduct a methodological exploration of the effect of attribute framing on marginal rates of substitution (MRS), including willingness to pay (WTP) from a discrete choice experiment (DCE), within the context of colorectal cancer screening preferences.

Methods: The survey, a fractional factorial design of a two-alternative, unlabeled experiment, was mailed to a sample of 1920 subjects in NSW, Australia. Participants were randomized to one of four alternative "frames" of information. Attributes included: accuracy of the test for finding cancers, accuracy of the test for finding large polyps, how good the test is at saying you don't have cancer, cost, dietary and medication restrictions and sample collection. A mixed logit model was used to estimate pre ferences; MRS between attributes, including WTP, was calculated.

Results: A total of 1157 surveys from 1920 (60.2%) were returned. Accuracy of the test for finding cancer was most likely to influence choice of test, followed by accuracy of the test for finding large polyps. Under some circumstances, framing of the attributes (e.g., cancers found vs. cancers missed) influenced the relative importance of attributes. Attribute framing significantly influenced estimates of WTP, and benefit: harm trade-offs that were calculated from MRS.

Conclusions: Attribute framing can influence willingness to pay and benefit: harm trade-offs from DCEs. Appropriate design and analysis methods should be explored to further characterize the influence and extent of framing in discrete choice studies.

Keywords: colorectal cancer, discrete choice experiments, preferences, screening.

Introduction

The context in which a decision is made can be an important determinant of outcomes. Context can be broadly thought of as including observable variables, characteristics of individuals, characteristics of the preference or choice task itself, and environmental features such as timing [1]. "Framing" is an example where the way in which information presented in a stated preference experiment can influence utility. Framing effects are well known [2–4]; however, their influence in discrete choice experiments (DCEs) is largely untested.

Recent reviews of discrete choice methodology [5–9] have identified methodological issues relating to preference elicitation that warrant further exploration. Some authors [7,9] discuss the importance of context in discrete choice studies, although others [6–8] discuss psychological issues such as use of heuristics, risk interpretation [5], and the implications of attribute framing.

This article considers one aspect of context: the impact of attribute framing in a DCE concerning preferences for immunochemical faecal occult blood tests (FOBTs) for screening for colorectal cancer (CRC).

Framing Risk

Discrete choice experiments (DCEs) often include risk or probabilities of outcomes as attributes [10]. When attributes are presented as risks, respondents are required to process probabilistic information and value outcomes within the bounds of rationality. The way in which probabilities are framed can influence an individual's decision-making behavior, for example, gains compared to losses, or relative risk compared to absolute risk [11,12]. Recent reviews have suggested that the implications on inclusion of risk or probability attributes, and attribute framing in DCEs should be investigated [5–9].

Outside DCEs, there is evidence that minor changes in the presentation or framing of prospects can have an impact upon the choices made. Kahneman and Tversky [4] found that altering the presentation of probabilities and outcomes can induce changes in individuals' interpretation of information and subsequent decision-making behavior. By changing the labelling of outcomes, as described in their famous "Asian disease" example [13], the more attractive option was dependent on whether outcomes were framed as lives saved, or lives lost. The options differed only in how the problem was framed. Similar framing effects have been demonstrated in other fields, including: public policy, taxation, health, contract negotiations, political preferences, and environmental policy [14–22].

Although identified as a potential methodological issue in the discrete choice literature, we are unaware of any published studies that have specifically examined the influence of attribute framing on choices made during DCEs in health. Two studies outside health, one in transportation [23,24] and one in environmental economics [25], have attempted to evaluate framing in DCEs. Hess et al. [23,24] evaluated whether positive and negative changes in travel time attribute levels from a prespecified reference alternative of a "current trip" were symmetrical. They found that increases and decreases in attribute levels were valued

Address correspondence to: Kirsten Howard, School of Public Health, Edward Ford Building (A27), University of Sydney, Sydney, NSW, 2006 Australia. E-mail: kirstenh@health.usyd.edu.au

10.1111/j.1524-4733.2008.00417.x

asymmetrically, indicating that gains and losses from a prespecified reference point did not have the same value. Although Rolfe et al. [25] purport to evaluate framing effects, they do not consider framing in the same context as implied above, that is, as a failure of description invariance. Instead, they evaluate the influence of the presence or absence of particular attributes or levels of attributes.

This current study was designed specifically as a methodological exploration of the influence of attribute framing in DCEs. The exploration of framing is set within the context of a DCE for preferences for screening for CRC. Attributes describing the potential benefits and harms of screening tests were presented in both positive and negative frames. Specifically, framing of the attributes was manipulated to be positive (the number of cancers found, the number of large polyps found) or negative (the number of cancers missed, the number of large polyps missed). The aim of this study was to conduct a methodological exploration of the effect of attribute framing on marginal rates of substitution (MRS), including willingness to pay (WTP), from a DCE.

Methods

Testing the effects of attribute framing was embedded within the design of a discrete choice study on preferences for FOBTs. The study followed the methods for conducting DCEs in health care as outlined by Ryan and Farrar [26].

Identification and Definition of the Attributes

A systematic review of the literature was conducted to identify the attributes of FOB testing for bowel cancer that were important to consumers. Goel et al. [27] found that characteristics associated with the process of testing, such as number of stool samples required, as well as cost and test accuracy characteristics, were factors mentioned as concerns by participants. Salkeld et al. [28] also identified similar characteristics: process attributes such as G.P. involvement in recommending, obtaining and checking the completed test; test result notification; test accuracy, sensitivity and specificity; the implications for early detection and treatment, including reduced risk of CRC mortality; and cost were all identified by respondents as factors that would influence them when considering an FOBT. Consistent with qualitative data, previous DCEs [29–31] have found that a number of different test attributes are important to consumers. These included test accuracy characteristics (deaths prevented [30], likelihood of a false positive test result, unnecessary colonoscopies) [30,31], process attributes (dietary and medication restrictions [29], G.P. supervision of the test [29], notification strategy for negative test results [30]), and cost [29,31].

These data suggested the following attributes were important to consumers: test sensitivity (accuracy of the test at finding cancers, accuracy of the test at finding large polyps, test specificity (how good the test is at saying you do *not* have cancer), out of pocket cost, dietary and medication restrictions required, and how the stool sample is collected (Table 1).

Framing of Attributes

The test sensitivity attributes for cancer and large polyps could be framed as either cancers found (true positive) or cancers missed (false negative). Test specificity (how good the test is at saying you do *not* have cancer) could also be presented in two different ways: number of people reassured that they do not have cancer—reassurance (true negative) and number of people who have unnecessary colonoscopies (false positive). Attribute descriptors are presented in Table 1; full attribute descriptions as presented in the survey are available from authors on request.

Table 1 Attribute levels

Attribute	Attribute levels	Presented in which frame?
1. Accuracy of test for cancers		
How many cancers the test will find	55 out of 100 cancers	Frame 1
	65 out of 100 cancers	Frame 3
	75 out of 100 cancers	
	85 out of 100 cancers	
How many cancers the test will miss	45 out of 100 cancers	Frame 2
	35 out of 100 cancers	Frame 4
	25 out of 100 cancers	
	15 out of 100 cancers	
2. Accuracy of the test for large polyps		
How many large polyps the test will find	35 out of 100 large polyps	Frame 1
	45 out of 100 large polyps	Frame 3
	55 out of 100 large polyps	
	65 out of 100 large polyps	
How many large polyps the test will miss	65 out of 100 large polyps	Frame 2
	55 out of 100 large polyps	Frame 4
	45 out of 100 large polyps	
	35 out of 100 large polyps	
3. How accurate the test is at saying you do NOT have cancer		
The number of people who are correctly reassured by the test that they do NOT have cancer	800 out of 1000 people	Frame 1
	850 out of 1000 people	Frame 4
	900 out of 1000 people	
	950 out of 1000 people	
The number of people who have unnecessary colonoscopies	60 out of 1000 people	Frame 2
	80 out of 1000 people	Frame 3
	100 out of 1000 people	
	120 out of 1000 people	
4. Cost	$20	All
	$30	
	$40	
	$50	
5. Dietary and medication restrictions	No	All
6. How the sample is collected	Brush stool surface gently then dab on test kit	All

Attribute Levels

The levels assigned to each of the four attributes are presented in Table 1. Attributes 5 (dietary and medication restrictions) and 6 (sample collection) were fixed across alternatives in a choice set.

A systematic review of the literature concerning the diagnostic accuracy of immunochemical FOBTs was conducted in September 2004 to inform the calculation of test accuracy levels. We restricted consideration of test accuracy to the two immunochemical FOBTs used in the Australian National Bowel Cancer Screening Pilot [32]; the "Inform" test (also known as "Insure") and the "Bayer Detect" test [33–37].

Estimates of test sensitivity, specificity, positive and negative predictive values were calculated for the tests for detection of cancers and detection of adenomas with a size greater than 10 mm (large polyps); these formed the basis of the test accuracy attributes levels.

At the time of the design of the DCE, the direct to consumer cost of immunochemical FOB tests was AUD$28. A plausible range around this cost was applied. Plausibility of the range for the cost attribute was imperative to ensure that respondents took

the questions seriously, as respondents were familiar with paying substantially less (around AUD$7) for the Rotary Bowelscan Hemoccult test (see *Study Sample* below) (Table 1).

Experimental Design

Each frame was a DCE that consisted of two alternatives with four attributes with four levels and two attributes with one level. Four attributes with four levels and two attributes with one level yields 256 combinations ($4\ \text{levels}^{4\ \text{attributes}} \times 1\ \text{levels}^{2\ \text{attributes}}$) (65,536 combinations with two alternatives). As is common practice, a systematic subset for two alternatives was selected using a fractional factorial design according to previously specified principles [38,39]. The design was chosen such that it minimized the number of questions with the same attribute levels (minimal overlap) between alternatives and ensured that the total number of times a given level appeared was balanced (level balance) [38,39]. The D-efficiency of the design for each frame indicated that the design was also efficient (D-errors < 0.0003) [39–41].

A pilot study of the DCE was conducted in 40 participants (10 per frame). The pilot survey indicated that respondents were able to complete 16 discrete choice questions without undue burden. Respondents were also able to understand and correctly interpret the attribute descriptions. The final fractional factorial design used a block design with a block size of 16; the 256 choice sets from each frame were divided into 16 blocks with 16 questions each; two questions were repeated to assess consistency, giving a total of 18 questions.

Survey Format

The postal survey used a dichotomous forced choice; participants had previously demonstrated a preference to be tested for bowel cancer by purchasing a Rotary Bowelscan FOBT test kit. Because this DCE was specifically designed to examine framing effects, rather than to inform CRC screening policy decisions, a forced choice was considered appropriate. An example of the choice task is provided in Appendix A. No financial incentives were provided, and a follow-up letter and copy of the questionnaire were resent at 6 weeks to nonresponders.

Study Sample and Setting

The sampling frame was men and women who had purchased an FOBT from the Central Coast Rotary Bowelscan Program in the previous 12 months (21,297 participants).

Sample size calculations were conducted as described in Louviere et al. [41]. A sample size of 480 for each survey frame was required to detect a true proportion, 10%, with a relative accuracy of 10% of P, and a probability (α) of between 95% and 99% (assuming a final response rate of 50%). Thus, a total sample of 1920 (four frames of 480 respondents) received the postal questionnaires. Participants were randomly assigned to a frame of the questionnaire (1–4) and then to one of the 16 groups within that frame.

Econometric Analysis

Mixed Logit Model

A mixed logit (ML) model was used for analysis. The statistical analysis of choice data is based on the random utility model [42–45]; each respondent faces a choice among j alternatives over s scenarios. The random utility theory (RUT) framework proposes that the utility that individual i derives from alternative j in scenario s can be separated into a systematic, or explainable, component and a stochastic (random) component. The utility function consists of an outcome (dependent) variable and explanatory variables. The outcome variable is the choice between two or more alternatives made by respondents for each profile in the questionnaire, although explanatory variables are observed or unobserved. Observed variables can be the attributes used to describe the tests, or other observed characteristics of respondents such as demographics. Unobserved variables are represented by a random component in the explanatory variables. The decision-making process within a DCE is therefore based on a comparison of indirect utility functions. In each choice set, the respondent is assumed to choose the alternative that leads to the higher level of utility, based on the notion that respondents behave as utility maximizers. The utility that individual i derives from alternative j in scenario s can be expressed

$$U_{isj} = X'_{isj}\beta_i + \varepsilon_{isj} \tag{1}$$

Where X_{isj} is a $K \times 1$ vector of explanatory variables and β_i is the vector of coefficients.

Conditional on β_i, a standard multinomial logit (MNL) results, assuming the disturbance terms are identically and independently distributed as extreme value. The probability that individual i chooses alternative j in scenario s is thus:

$$P_{isj} = \frac{\exp(X'_{isj}\beta_i)}{\sum_k \exp(X'_{isk}\beta_i)} \tag{2}$$

This MNL model specification can be generalized to allow for possible heterogeneity across individuals. In this generalization

$$\beta_{ki} = Z'_i\bar{\beta}_k + \sigma_k\omega_{ki}, \quad k = 1, \ldots K \tag{3}$$

where Z_i is a vector of observed characteristics of the respondent i, the β_k are parameter vectors and $\sigma_k\omega_{ki}$ represents unobserved heterogeneity in the preference weights. The resultant model is termed a random parameter or ML model. The ω_{ki} follow standard normal distributions, and are independent of ε_{isj}, and of each other. Under this model β_{ki} can vary across individuals, but not across the repeated choices made by that individual. Thus, the common "panel" structure of the data is accounted for by introducing error correlation over choice scenarios.

Mixed logit have a number of properties that are intuitively appealing: they can take account of parameter heterogeneity across a population by using random, rather than fixed parameters and they can take account of multiple correlated responses from single individuals, by deriving the individual's conditional distribution based (within sample) on their choices [46–48]. They have recently become popular in the literature, and are gradually being used more frequently in the analysis of stated preferences for health-care services [49–52].

Model Estimation

Table 2 indicates the variables included in the MNL and ML models.

Respondents chose between two alternatives in each of the 16 unlabelled choice scenarios. The conceptual framework for DCEs draws on Lancaster's economic theory of value [53,54] as well as on RUT [43–45]. Random utility models were used to define the utility of choice alternatives, as a function of the attributes. In each choice set, the respondent is assumed to choose the alternative that leads to the higher level of utility, based on the notion that respondents behave as utility maximizers.

$$\begin{aligned} V_{Test} = {} & \beta_0 + \beta_{\text{cafind}}\text{CAFIND} + \beta_{\text{lpfind}}\text{LPFIND} + \beta_{\text{reass}}\text{REASS} + \\ & \beta_{\text{cost}}\text{COST} + \beta_{\text{age}}\text{AGE} + \beta_{\text{sex}}\text{SEX} + \beta_{\text{risk}}\text{RISK} + \\ & \beta_{\text{famhistory}}\text{FAMHISTORY} + \varepsilon_{T1} \end{aligned} \tag{4}$$

Table 2 Variables and descriptions for MNL and ML models

Model variables	
Variables	Description
Random parameters (in ML only)	
CAFIND1*	How many cancers the test will find (out of 100 cancers) (Frame 1)
CAFIND3*	How many cancers the test will find (out of 100 cancers) (Frame 3)
CAMISS2*	How many cancers the test will miss (out of 100 cancers) (Frame 2)
CAMISS4*	How many cancers the test will miss (out of 100 cancers) (Frame 4)
LPFIND1*	How many large polyps the test will find (out of 100 cancers) (Frame 1)
LPFIND3*	How many large polyps the test will find (out of 100 cancers) (Frame 3)
LPMISS2*	How many large polyps the test will miss (out of 100 cancers) (Frame 2)
LPMISS4*	How many large polyps the test will miss (out of 100 cancers) (Frame 4)
REASS1*	How many people correctly reassured by the test that they do not have cancer (out of 1000 people tested) (Frame 1)
REASS4*	How many people correctly reassured by the test that they do not have cancer (out of 1000 people tested) (Frame 4)
UNCOL2*	How many people have unnecessary colonoscopies (out of 1000 people tested) (Frame 2)
UNCOL3*	How many people have unnecessary colonoscopies (out of 1000 people tested) (Frame 3)
Nonrandom parameters	
Constant1	Alternative specific constant (Frame 1)
Constant2	Alternative specific constant (Frame 2)
Constant3	Alternative specific constant (Frame 3)
Constant4	Alternative specific constant (Frame 4)
COST1	Cost of the test (Frame 1)
COST2	Cost of the test (Frame 2)
COST3	Cost of the test (Frame 3)
COST4	Cost of the test (Frame 4)
AGE	Age (continuous)
SEX	Sex (0 = female, 1 = male)
RISK	Perceived risk of colorectal cancer (low/average [0]; higher than average [1])
FAMHISTORY	Has anyone in your family had colorectal cancer (no [0]; yes [1])

*Normal distribution applied in analyses.
ML, mixed logit; MNL, multinomial logit.

The utility functions estimated included random and nonrandom parameters. Random parameters need to take account of the distributional assumptions placed upon them in the model; the true distribution of a random parameter is not known so an analytical distribution—such as normal, lognormal or triangle—is modeled as an approximation [47,48]. The utility function is estimated such that the outcome variable is the value in moving from one test to another, within each frame of information. In this analysis, normal distributions were applied to all random parameters (Table 2).

The β parameters can be interpreted as relative importance of the attributes, and were used to assess the effect of framing on attribute importance, and on the MRS between attributes, including WTP.

Models were evaluated for goodness of fit using the likelihood ratio chi-square statistic for the global test of zero model coefficients, the McFadden's pseudo R^2, and Akaike's information criterion (AIC). Model results are expressed as parameter estimates, 95% confidence intervals and *P*-values. Model variables were effects coded and all analyses were conducted using 10,000 Halton draws in NLOGIT Version 4.0.

Results

Between December 2004 and April 2005, 1157 from 1920 randomly selected Rotary Bowelscan participants completed and returned the questionnaire, giving an overall response rate of 60.2%. A summary of respondent demographic characteristics is presented in Table 3. There was no significant difference between the demographic characteristics of respondent groups. Overall, <1% of respondents (11 from 1157) failed the two consistency questions. There was no difference in model parameter estimates with and without these respondents. Therefore, all respondents were included in analyses. Table 4 presents the results of the basic MNL model and the ML model.

Results for both the MNL and ML models indicated that attributes (of the tests) were highly statistically significant. Accuracy of the test for finding cancer was the attribute most likely to influence choice of test, followed by accuracy of the test for finding large polyps, and cost. How good the test is at saying you don't have cancer was less important in determining choice of test. Demographic characteristics (age, sex, perceived risk of CRC, and family history) did not significantly influence choice of test.

Additional results from the ML model pertained to the SD of the random parameters. The insignificant parameter estimate for the estimated SD for LPMISS2 indicated that the dispersion around the mean is statistically equal to zero; thus, all distributional information for this parameter was contained within the mean. The statistically significant estimates for derived SD for random parameters for all other parameters suggested the existence of heterogeneity around the mean parameter over the sampled population. The ML model was statistically significant compared to a base model assuming equal choice shares only (with a chi-square equal to 60,709 with 40 degrees of freedom and a *P*-value equal to zero) and had a pseudo R^2 of 0.84. The statistical significance of the model was maintained when the ML model was compared to the MNL model (chi-square equal to 2539.26 $[-2 \times [-6963.88 - (-5694.25)]$ with 16 degrees of freedom, $P < 0.0001$]), indicating that the ML model was significantly better than the MNL model. In addition, the reduction in AIC indicated that this improvement remained after penalizing for the loss of parsimonious specification in moving from the MNL to ML.

Value of Cancers Found versus Cancers Missed

The absolute value of the β for the attribute "cancers found" was compared to the absolute value of β for the attribute "cancers missed" in two circumstances: first, when the specificity attribute "how accurate the test is at saying you do not have cancer" was

Table 3 Characteristics of respondents in each group

Characteristics	Frame 1		Frame 2		Frame 3		Frame 4	
	N = 298	%	N = 291	%	N = 278	%	N = 290	%
Mean age (range; SD)	63 (40–90; 11.3)		62 (32–88; 11.0)		63 (37–89; 10.4)		63 (37–92; 11.1)	
Response rate	62.1%		60.6%		57.2%		60.4%	
Sex (F:M)	168:130	56:44	177:114	61:39	159:119	57:43	166:124	57:43
Education								
Primary school	1	<1	5	2	6	2	9	3
Some high school	60	21	41	14	45	17	55	20
Completed high school	79	28	76	27	65	24	58	21
TAFE/technical/trade/diploma	86	30	91	32	77	28	83	30
Degree (university or college)	61	21	74	26	80	29	74	26
Employment								
Full-time	59	21	56	21	54	20	51	19
Part-time/casual	35	13	44	16	53	20	36	13
Home duties	20	7	15	6	18	7	16	6
Self-funded retirement	70	25	72	27	78	29	78	29
Pension	92	33	78	29	66	25	89	33
Not working	3	1	4	1	0	0	3	1
Private health insurance	215	75	229	80	220	81	219	79
Family history of CRC	74	26	78	28	56	21	69	24
Know someone with CRC	157	56	157	56	168	63	166	59
Self-perceived risk of colorectal cancer								
A lot/lower than average	56	20	56	20	52	19	61	21
Average	175	61	152	56	180	67	171	60
A lot/higher than average	54	19	65	24	38	14	52	18

CRC, colorectal cancer.

expressed as "number reassured" (comparison of Frames 1 and 4), and second, when it is framed as "number of unnecessary colonoscopies" (comparison of Frames 2 and 3).

When the specificity attribute "how accurate the test is at saying you do not have cancer" was expressed as "number reassured" the absolute value for "cancers found" was 0.2157 (95% CI 0.2022–0.2293), compared to "cancers missed" at 0.2065 (95% CI 0.1948–0.2182). Thus, as the confidence intervals overlap, framing of the test sensitivity attribute (cancers found compared to cancers missed) did not significantly influence the valuation of this attribute.

When the specificity attribute "how accurate the test is at saying you do not have cancer" was expressed as "unnecessary colonoscopies," the absolute value for "cancers found" was 0.2160 (95% CI 0.1965–0.2355), compared to "cancers missed" at 0.1744 (95% CI 0.1568–0.1920). Here, confidence intervals do not overlap; framing of the test sensitivity attribute significantly influenced its valuation.

Value of Large Polyps Found versus Large Polyps Missed

A similar pattern of framing effects was seen for "large polyps found" and "large polyps missed." When the specificity attribute "how accurate the test is at saying you do not have cancer" was expressed as "number reassured," the confidence intervals of β coefficients overlap, and framing effects were not significant.

When the specificity attribute "how accurate the test is at saying you do not have cancer" was expressed as "unnecessary colonoscopies," confidence intervals of β coefficients do not overlap; framing significantly influenced the valuation of test accuracy for large polyps; "large polyps found" were valued more highly than "large polyps missed."

MRS between Attributes

Willingness to pay estimates in Table 5 were calculated from the conditional parameter estimates in the ML model. Estimates of WTP for test attributes were significantly influenced by attribute framing for all comparisons of comparable attributes, as evidenced by the lack of overlapping confidence intervals. For example, respondent's WTP for an extra cancer found was significantly higher when test specificity attribute was presented as number people with unnecessary colonoscopies. In the absence of framing effects, the WTP for one extra cancer found (e.g., $11.45 [$11.24–$11.68]) should also have been the same as the WTP for one fewer cancer missed (e.g., $9.81 [$9.65–$9.98]).

Table 6 indicates the benefit : harm ratios, as calculated by MRS between attributes. These ratios indicated the potential harms that respondents were willing to trade off against one unit of increased benefit, as measured by one extra cancer found or one fewer cancer missed. If framing effects exist, one would expect there to be significant differences in the potential harms people are willing to accept to gain one extra cancer found or one fewer cancer missed. This is demonstrated in Table 6, as confidence intervals of benefit: harm ratios do not overlap. For example, in the absence of framing effects, the benefit:harm ratio of "more cancers found:unnecessary colonoscopies" would equal the ratio of "fewer cancers missed: unnecessary colonoscopies." When the test sensitivity was presented as "cancers found," respondents were willing to accept 22.8 more unnecessary colonoscopies (95% CI 17.9–27.7) for every extra cancer that the test found. When the test sensitivity was presented as "cancers missed," respondents were willing to accept significantly less potential harm: 10.4 more unnecessary colonoscopies (95% CI 8.2–12.5) for every fewer cancer missed by the test.

Discussion

Although framing has been identified as a potential methodological issue in the discrete choice literature [5–9], there has been no published study in health that has examined the influence of attribute framing on choices made during DCEs.

Results from the current study demonstrated that attribute framing significantly influenced respondent WTP for changes in

Table 4 Results from multinomial logit (MNL) and mixed logit (ML) models

		MNL model					ML model				
				95% CI					95% CI		
Variables		B-coeff	SE	Lower	Upper	*P*	B-coeff	SE	Lower	Upper	*P*
Random parameters											
CAFIND1	Mean	0.1235	0.0038	0.1160	0.1309	<0.00001	0.2157	0.0069	0.2022	0.2293	<0.00001
	SD						0.1082	0.0054	0.0976	0.1187	<0.00001
CAFIND3	Mean	0.1423	0.0043	0.1338	0.1508	<0.00001	0.2160	0.0099	0.1965	0.2355	<0.00001
	SD						0.1730	0.0060	0.1613	0.1848	<0.00001
CAMISS2	Mean	−0.1410	0.0042	−0.1492	−0.1328	<0.00001	−0.1744	0.0090	−0.1920	−0.1568	<0.00001
	SD						0.1145	0.0120	0.0911	0.1380	<0.00001
CAMISS4	Mean	−0.1079	0.0034	−0.1145	−0.1013	<0.00001	−0.2065	0.0060	−0.2182	−0.1948	<0.00001
	SD						0.1968	0.0107	0.1759	0.2177	<0.00001
LPFIND1	Mean	0.0479	0.0029	0.0422	0.0535	<0.00001	0.0761	0.0045	0.0673	0.0848	<0.00001
	SD						0.0596	0.0061	0.0476	0.0716	<0.00001
LPFIND3	Mean	0.0577	0.0032	0.0514	0.0639	<0.00001	0.0881	0.0059	0.0765	0.0996	<0.00001
	SD						0.0484	0.0060	0.0367	0.0601	<0.00001
LPMISS2	Mean	−0.0523	0.0030	−0.0581	−0.0465	<0.00001	−0.0645	0.0030	−0.0703	−0.0586	<0.00001
	SD						0.0050	0.0111	−0.0169	0.0268	0.6568
LPMISS4	Mean	−0.0408	0.0026	−0.0458	−0.0358	<0.00001	−0.0884	0.0080	−0.1042	−0.0727	<0.00001
	SD						0.0868	0.0081	0.0709	0.1026	<0.00001
REASS1	Mean	0.0094	0.0005	0.0084	0.0103	<0.00001	0.0249	0.0013	0.0223	0.0275	<0.00001
	SD						0.0319	0.0016	0.0288	0.0350	<0.00001
REASS4	Mean	0.0071	0.0005	0.0062	0.0081	<0.00001	0.0080	0.0016	0.0048	0.0111	<0.00001
	SD						0.0276	0.0017	0.0242	0.0310	<0.00001
UNCOL2	Mean	−0.0165	0.0013	−0.0191	−0.0140	<0.00001	−0.0200	0.0025	−0.0248	−0.0152	<0.00001
	SD						0.0210	0.0020	0.0171	0.0249	<0.00001
UNCOL3	Mean	−0.0078	0.0013	−0.0103	−0.0054	<0.00001	−0.0122	0.0030	−0.0181	−0.0064	<0.00001
	SD						0.0276	0.0030	0.0218	0.0335	<0.00001
Nonrandom parameters											
Constant1		−0.0165	0.1321	−0.2754	0.2425	0.9008	−0.0169	0.1561	−0.3227	0.2890	0.9138
Constant2		−0.0996	0.1304	−0.3551	0.1559	0.4449	−0.1005	0.1603	−0.4146	0.2137	0.5308
Constant3		−0.1064	0.1317	−0.3644	0.1517	0.4192	−0.1062	0.1598	−0.4194	0.2070	0.5064
Constant4		0.0493	0.1311	−0.2076	0.3062	0.7068	0.0501	0.1581	−0.2598	0.3600	0.7513
COST1		−0.0185	0.0026	−0.0236	−0.0135	<0.00001	−0.0338	0.0026	−0.0390	−0.0287	<0.00001
COST2		−0.0165	0.0028	−0.0219	−0.0111	<0.00001	−0.0186	0.0029	−0.0244	−0.0128	<0.00001
COST3		−0.0135	0.0028	−0.0189	−0.0081	<0.00001	−0.0201	0.0032	−0.0263	−0.0138	<0.00001
COST4		−0.0208	0.0024	−0.0255	−0.0161	<0.00001	−0.0455	0.0031	−0.0517	−0.0394	<0.00001
AGE		0.0009	0.0020	−0.0030	0.0047	0.6559	0.0015	0.0022	−0.0029	0.0059	0.5069
SEX		−0.0387	0.0432	−0.1234	0.0460	0.3708	−0.0383	0.0514	−0.1391	0.0624	0.4560
RISK		−0.0080	0.0616	−0.1287	0.1126	0.8961	−0.0084	0.0811	−0.1673	0.1505	0.9175
FAMHISTORY		0.0545	0.0551	−0.0536	0.1626	0.3229	0.0540	0.0639	−0.0712	0.1791	0.3980
McFadden's R^2 (pseudo R^2)				0.18043					0.8416		
AIC				0.806					0.309		
Log-likelihood				−6963.88					−5694.25		

AIC, Akaike's information criterion.

attributes. Similarly, the benefit to harm trade-offs from MRS between test accuracy attributes "cancers found (or missed-):people reassured" and "cancers found (or missed):unnecessary colonoscopies" were also significantly different depending upon whether test sensitivity was expressed as cancers found or cancers missed. These results are consistent with other studies: Tversky and Kahneman [13] demonstrated the effect of framing in their "Asian disease" experiment, where information on interventions (a certain and a risky option with the same expected value) was presented in terms of "lives saved" or "lives lost." Results indicated that framing outcomes as "lives saved" rather than "lives lost" led to large differences in choice probabilities,

Table 5 Willingness to pay (WTP) for test characteristics

Attribute	WTP calculation (β/β)	Mean WTP ($)	Lower 95% CI	Upper 95% CI
$/extra cancer found (F1)	$\beta_{\text{cancers found-F1}}/\beta_{\text{cost-F1}}$	$6.43	$6.35	$6.51
$/extra cancer found (F3)	$\beta_{\text{cancers found-F3}}/\beta_{\text{cost-F3}}$	$11.45	$11.24	$11.66
$/missed cancer avoided (F2)	$\beta_{\text{cancers missed-F2}}/\beta_{\text{cost-F2}}$	$9.81	$9.65	$9.98
$/missed cancer avoided (F4)	$\beta_{\text{cancers missed-F4}}/\beta_{\text{cost-F4}}$	$4.93	$4.83	$5.04
$/extra large polyp found (F1)	$\beta_{\text{LP found-F1}}/\beta_{\text{cost-F1}}$	$2.27	$2.24	$2.31
$/extra large polyp found (F3)	$\beta_{\text{LP found-F3}}/\beta_{\text{cost-F3}}$	$4.38	$4.33	$4.43
$/missed large polyp avoided (F2)	$\beta_{\text{LP missed-F2}}/\beta_{\text{cost-F2}}$	$3.47	$3.47	$3.48
$/missed large polyp avoided (F4)	$\beta_{\text{LP missed-F4}}/\beta_{\text{cost-F4}}$	$2.02	$1.98	$2.07
$/extra person reassured that they don't have cancer (F1)	$\beta_{\text{reassured-F1}}/\beta_{\text{cost-F1}}$	$0.71	$0.69	$0.73
$/extra person reassured that they don't have cancer (F4)	$\beta_{\text{reassured-F4}}/\beta_{\text{cost-F4}}$	$0.23	$0.22	$0.25
$/unnecessary colonoscopy avoided (F2)	$\beta_{\text{unnec. colonosc-F2}}/\beta_{\text{cost-F2}}$	$1.13	$1.10	$1.15
$/unnecessary colonoscopy avoided (F3)	$\beta_{\text{unnec. colonosc-F3}}/\beta_{\text{cost-F3}}$	$0.68	$0.66	$0.71

Table 6 MRS between test characteristics

Benefit:harm ratio	MRS calculation (β/β)	Mean MRS	Lower 95% CI	Upper 95% CI
More cancers found:reduction in people reassured (F1)	$\beta_{\text{cancers found-F1}}/\beta_{\text{reass-F1}}$	8.6162	3.4072	13.8253
Fewer cancers missed:reduction in people reassured (F4)	$\beta_{\text{cancers missed-F4}}/\beta_{\text{reass-F4}}$	24.2039	18.7398	29.6681
More cancers found:unnecessary colonoscopies (F3)	$\beta_{\text{cancers found-F3}}/\beta_{\text{uncol-F3}}$	22.7919	17.8861	27.6977
Fewer cancers missed:unnecessary colonoscopies (F2)	$\beta_{\text{cancers missed-F2}}/\beta_{\text{uncol-F2}}$	10.3579	8.2341	12.4818

MRS, marginal rates of substitution.

with substantially more people favoring the certain option when it was framed as lives saved (rather than lives lost). Physicians, students, and clinic patients made different choices of treatments for lung cancer (surgery or radiation therapy) depending upon whether outcomes were framed as mortality or survival rates. Treatment options where outcomes were presented as survival were viewed more favorably [55]. The increased WTP for cancers found rather than missed cancers avoided reflects an overweighting of a positive outcome and underweighting of a negative outcome avoided [4]; people are not generating an expected value as the product of objective probability multiplied by value of the outcome; instead the value of outcomes is weighted by a "decision weight" rather than an objective probability [4].

So how do we best deal with the effects of attribute framing? Unfortunately, no simple answer exists. Druckman [56], in a repeat of Tversky and Kahneman's "Asian disease" [13] framing experiment, has suggested that presentation of both frames of information may overcome some of the framing effect. In an experiment which examined alternative frames of information, including a combined mortality/survival presentation, he found that 68% of respondents chose the risk-averse alternative with the survival frame, compared to 23% with the mortality frame (consistent with Tversky and Kahneman's original results). Forty-four percent of the respondents with the "both" format chose the risk-averse alternative, approximately midway between the survival and mortality formats. Although his experiment was based on calculating the proportions of respondents choosing different options, it is possible that presenting both frames of attribute information in a DCE may also help overcome framing effects in this context by explicitly valuing positive and negative effects separately. This remains to be tested in a DCE context.

Pivot designs [24,57,58] make use of respondents' experiences as an explicit reference alternative within the choice set. The reference alternative acts to frame the decision context of the choice task within some existing remembered context of the individual and hence ". . . makes preference–revelation more meaningful at the level of the individual, consistent with prospect theory." [23] Attribute levels of an alternative are expressed as a gain or loss relative to an individual's reference alternative. Utility functions (and therefore models) are specified with separate coefficients for increases and decreases in an attribute relative to some reference point, thereby allowing for asymmetrical valuations of gains and losses. Although not directly applicable to the problem presented in this study where one level of an attribute can be described in multiple ways, we may be able to apply these design and analysis techniques to better understand the issue of framing.

Within a policy and service delivery context, there are important implications for different estimates of willingness to pay and MRS with alternative attribute presentations. Development of methods to assess and account for the magnitude of effect introduced by attribute framing are necessary.

So what are the implications for DCEs in health care and where do framing effects fit into the conventional process for conducting and analyzing DCEs [26]? To begin to understand the influence of framing, we firstly need to explicitly look for it in the studies we conduct. The existing criteria for design and analysis of DCEs [26] do not consider attribute framing; a complementary set of criteria is proposed on the right hand side of Figure 1. Figure 1 is intended to provide a possible set of addition steps that could be taken to design a study to further characterize framing effects.

Attributes likely to be influenced by framing effects such as risk, probabilistic or cost attributes [5–9] should be identified a priori (A). After identification of such attributes and the relevant levels for alternative frames, explicit consideration should be given during the design of DCEs (B) such that a design allowing characterization of framing effects can be implemented. Although we recognize that these processes may not be possible for all studies, we suggest that if researchers elect not to characterize framing effects in their DCEs, they should explain and justify the approach taken, and apply it consistently throughout their study.

The final step in Figure 1 involves the appropriate specification of advanced models, such as ML models to adequately capture respondent preferences. Use of ML models also has implications for design of stated-preference choice experiments, and there is a growing literature concerning itself with the development of statistically efficient designs appropriate for these models [38,59–63]. So what can decision-makers do in the interim? Until we know more about framing effects in DCEs, and how, if at all, we may be able to mathematically adjust for framing, it may be useful for decision-makers to propose guidelines for presentation of results of DCEs. For example, to facilitate consistent interpretation of DCE results, in the context of framing effects, one practical suggestion is that decision-makers could require that all attributes be expressed in the same direction (all in the positive or all in the negative frame).

This is one of the first studies to examine framing effects in DCEs. Because we are at such an early stage of examining framing in DCEs, it is important to ascertain whether the effects reported in this study are also present across other studies, in different contexts, and with different respondent populations. Future discrete choice studies may also care to examine framing to assess whether the effects on WTP and MRS seen here are indeed a phenomena that occur in discrete choice studies more generally. We recognize that more research is needed in this area, and that the current study has raised a number of issues that warrant further exploration. It is possible that the magnitude of framing effects may vary with respondent age, or with other demographic characteristics, such as experience; temporality of the attribute (for example, how far in the future a cancer may be found or missed) may also influence the value individuals attach to that attribute, and subsequently the extent of attribute framing. Prior experience of our study population with FOBT may mean that they value attributes differently to the general population. Nevertheless, the question remains whether attribute framing differentially affects naive or experienced respondents. Some evidence from medical decision-making suggests that experience does not help with interpretation or application of risk information to decision-making, with examples of framing

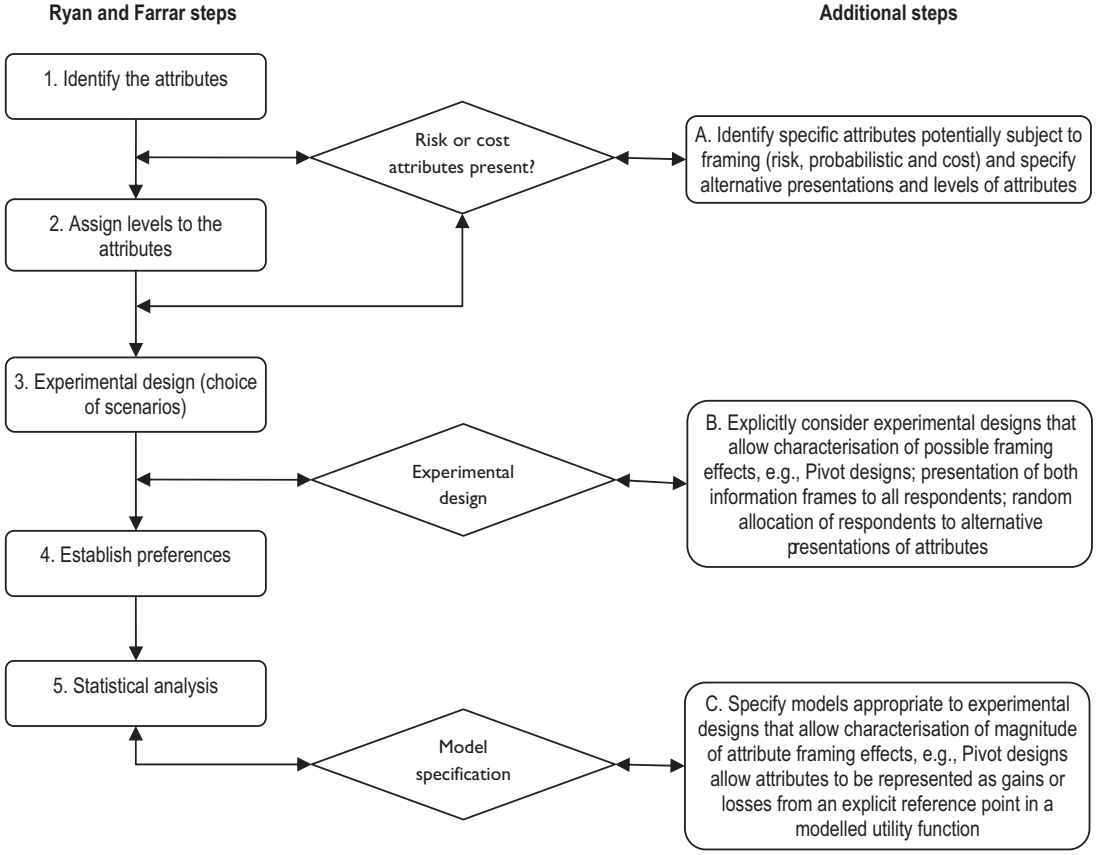

Figure 1 Ryan and Farrar criteria and additional proposed criteria required for explicit consideration of the influence of framing.

effects in both naive and experienced respondents [2]. For example, physicians, students, and clinic patients made different choices of treatments for lung cancer (surgery or radiation therapy) depending upon whether outcomes were framed as mortality or survival rates [55]. Consistent patterns of responses were made regardless of the level of experience of respondents, or their familiarity with the subject matter. Nevertheless, whether this holds true in the context of a DCE is unclear at this stage. In addition, a number of study design and administration issues may also influence the extent of framing; our study used a forced choice design administered as a postal survey; however, it is unclear whether a design with an opt-out choice, and/or a face to face survey may have led to different patterns of framing effects. Further quantification of the magnitude and pattern of framing effects in health-care DCEs under different circumstances, with different respondent populations and using different survey designs and administration techniques, will facilitate the development of appropriate DCE design and analysis methods.

Conclusions

In conclusion, this study demonstrates that framing of attributes can significantly influence estimation of WTP, and MRS between attributes. Ongoing research to ascertain the existence of these effects in other decision contexts, and ongoing research on appropriate design and analysis methods will allow further quantification of the magnitude of the influence of framing effects in DCEs.

This study was funded by the Australian National Health and Medical Research Council, Program Grants 211205, and 402764 for the Screening and Test Evaluation Program. We also acknowledge the support of Walter Leijten and staff from Rotary Bowelscan (Rotary Club of East Gosford, District 9680).

Source of financial support: Provided in part by the Program Grants 211205 and 402764 from the National Health and Medical Research Council, Australia.

References

1 Louviere JJ, Street D, Carson R, et al. Dissecting the random component of utility. Market Lett 2002;13:177–93.
2 Tversky A. Contrasting rational and psychological principles in choice. In: Zeckhauser RJ, Keeney RL, Sebenius JK, eds. Wise Choices: Decisions, Games and Negotiations. Boston, MA: Harvard Business School Press, 1996.
3 Starmer C. Developments in non-expected utility theory: the hunt for a descriptive theory of choice under risk. J Econ Lit 2000; 38:332–82.
4 Kahneman D, Tversky A. Prospect theory: an analysis of decision under risk. Econometrica 1979;27:263–91.
5 Ryan M, Gerard K. Using discrete choice experiments to value health care programmes: current practice and future research reflections. Appl Health Econ Health Policy 2003;2:55–64.
6 Lloyd AJ. Threats to the estimation of benefit: are preference elicitation methods accurate? Health Econ 2003;12:393–402.
7 Ryan M, Amaya-Amaya M. "Threats" to and hopes for estimating benefits. Health Econ 2005;14:609–19.

8 Bryan S, Dolan P. Discrete choice experiments in health economics. For better or for worse? Eur J Health Econ 2004;5:199–202.
9 Swait JD, Adamowicz W, Hanemann M, et al. Context dependence and aggregation in disaggregate choice analysis. Market Lett 2002;13:195–205.
10 Ryan M, Skatun D. Modelling non-demanders in choice experiments. Health Econ 2004;13:397–402.
11 Edwards A, Elwyn G, Covey J, et al. Presenting risk information—a review of the effects of "framing" and other manipulations on patient outcomes. J Health Commun 2001;6: 61–82.
12 Edwards A, Elwyn G, Mulley A. Explaining risks: turning numerical data into meaningful pictures. BMJ 2002;324:827–30.
13 Tversky A, Kahneman D. The framing of decisions and the psychology of choice. Science 1981;211:453–8.
14 Frederickson JR, Waller W. Carrot or stick? Contract frame and use of decision-influencing information in a principal-agent setting. J Accounting Res 2005;43:709–33.
15 Ovaskainen V, Kniivila M. Consumer versus citizen preferences in contingent valuation: evidence on the role of question framing. Aust J Agric Resour Econ 2005;49:379–94.
16 McCaffery EJ, Baron J. Framing and taxation: evaluation of tax policies involving household composition. J Econ Psychol 2004; 25:679–705.
17 Druckman JN. Political preference formation: competition, deliberation, and the (ir)relevance of framing effects. Am Polit Sci Rev 2004;98:671–86.
18 Rege M, Telle K. The impact of social approval and framing on cooperation in public good situations. J Public Econ 2004;88: 1625–44.
19 Park ES. Warm-Glow versus cold-prickle: a further experimental study of framing effects on free-riding. J Econ Behav Organ 2000;43:405–21.
20 Miller CA. The dynamics of framing environmental values and policy: four models of societal processes. Environ Values 2000;9: 211–33.
21 Sonnemans J, Schram A, Offerman T. Public good provision and public bad prevention: the effect of framing. J Econ Behav Organ 1998;34:143–61.
22 Johannesson M, Johansson PO. Saving Lives in the present versus saving lives in the future—is there a framing effect? J Risk Uncertain 1997;15:167–76.
23 Hess S, Rose JM, Hensher DA. Asymmetrical preference formation in willingness to pay estimates in discrete choice models. Transport Res E-Log 2008;44:847–63.
24 Hess S, Rose JM, Hensher DA. Asymmetrical Preference Formation in Willingness to Pay Estimates in Discrete Choice Models. Sydney: University of Sydney, 2006. Report No.: ITLS-WP-06-12.
25 Rolfe J, Bennett J, Louviere J. Stated values and reminders of substitute goods: testing for framing effects with choice modelling. Aust J Agric Resour Econ 2002;46:1–20.
26 Ryan M, Farrar S. Using conjoint analysis to elicit preferences for health care. BMJ 2000;320:1530–3.
27 Goel V, Gray R, Chart P, et al. Perspectives on colorectal cancer screening: a focus group study. Health Expect 2004;7:51–60.
28 Salkeld G, Solomon MJ, Short L, Ward J. Measuring the importance of attributes that influence consumer attitudes to colorectal cancer screening. Aust N Z J Public Health 2003;73:128–32.
29 Salkeld G. The veil of experience: do consumers prefer what they know best? Health Econ 2000;9:267–70.
30 Salkeld G, Solomon M, Short L, et al. Evidence-based consumer choice: a case study in colorectal cancer screening. Aust N Z J Public Health 2003;27:449–55.
31 Gyrd-Hansen D, Sogaard J. Analysing public preferences for cancer screening programs. Health Econ 2001;10:617–34.
32 Australian Government Department of Health and Ageing. Australia's Bowel Cancer Screening Pilot and Beyond. Final Evaluation Report. Canberra: Commonwealth of Australia, 2005.
33 Young G, St John DJ, Cole SR, et al. Prescreening evaluation of a brush-based faecal immunochemical test for haemoglobin. J Med Screen 2003;10:123.
34 Wong WM, Lam SK. Cheung KL, et al. Evaluation of an automated immunochemical fecal occult blood test for colorectal neoplasia detection in a Chinese population. Cancer 2003;97: 2420–4.
35 Rozen P, Knaani J, Samuel Z. Performance characteristics and comparison of two immunochemical and two guaiac fecal occult blood screening tests for colerectal neoplasia. Dig Dis Sci 1997;42:2064–71.
36 Allison J, Tekawa I, Ransom L, Adrain A. A comparison of fecal occult-blood tests for colorectal cancer screening. N Engl J Med 1996;334:155–9.
37 Greenberg PD, Bertario L, Gnauck R, et al. A prospective multicenter evaluation of new fecal occult blood tests in patients undergoing colonoscopy. Am J Dig Dis 2000;95:1331–8.
38 Huber J, Zwerina K. The importance of utility balance in efficient choice design. J Mark Res 1996;XXXIII:307–17.
39 Viney R, Savage E, Louviere J. Empirical investigation of experimental design properties of discrete choice experiments in health care. Health Econ 2005;14:349–62.
40 Rose JM, Bliemer MCJ. The Design of Stated Choice Experiments: The State of Practice and Future Challenges. Sydney: University of Sydney, 2004. Report No.: ITS-WP-04-09.
41 Louviere J, Hensher DA, Swait JD. Stated Choice Methods—Analysis and Application. Cambridge: Cambridge University Press, 2000.
42 McFadden D. Econometric models of probabilistic choice. In: Manski CF, McFadden D, eds. Structural Analysis of Discrete Data with Economic Applications. Boston: MIT Press, 1981.
43 Thurstone L. A law of comparative judgement. Psychol Rev 1927;4:273–86.
44 McFadden D. Conditional logit analysis of qualitative choice behavior. In: Zarembka P, ed. Frontiers of Econometrics. New York: Academic Press, 1973.
45 Manski CF. The structure of random utility models. Theory Decis 1977;8:229–54.
46 Hensher DA, Greene WH. The Mixed Logit Model: The State of Practice. Sydney: University of Sydney, 2002. Report No.: ITS-WP-02-01.
47 Hensher DA, Greene WH. The mixed logit model: the state of practice. Transportation, 2003;30:133–76.
48 Hensher DA, Rose JM, Greene WH. Applied Choice Analysis. A Primer. Cambridge: Cambridge University Press, 2005.
49 Johnson FR, Banzhaf MR, Desvousges WH. Willingness to pay for improved respiratory and cardiovascular health: a multiple-format, stated-preference approach. Health Econ 2000;9:295–317.
50 Iraguen P, de Dios OJ, Iraguen P, Dios Ortuzar J. Willingness-to-pay for reducing fatal accident risk in urban areas: an internet-based web page stated preference survey. Accid Anal Prev 2004;36:513–24.
51 Hall J, Fiebig DG, King MT, et al. What influences participation in genetic carrier testing? Results from a discrete choice experiment. J Health Econ 2006;25:520–37.
52 Arana JE, Leon CJ, Quevedo JL. The effect of medical experience on the economic evaluation of health policies. A discrete choice experiment. Soc Sci Med 2006;63:512–24.
53 Lancaster K. A new approach to consumer theory. J Polit Econ 1966;74:134–57.
54 Lancaster K. Consumer Demand: A New Approach. New York: Columbia University Press, 1971.
55 McNeil BJ, Pauker SG, Sox H, Tversky A. On the elicitation of preferences for alternative therapies. N Engl J Med 1982;306: 1259–62.
56 Druckman JN. Evaluating framing effects. J Econ Psychol 2001; 22:91–101.
57 Train K, Wilson WW. Econometric Analysis of Stated-Preference Experiments Constructed from Revealed-Preference Choices. Berkeley, CA: University of California, Berkeley, 2006.
58 Greene WH, Hensher DA, Rose JM. Accounting for heterogeneity in the variance of unobserved effects in mixed logit models. Transport Res B-Meth 2006;40:75–92.

59 Street D, Burgess L. Optimal and near-optimal pairs for the estimation of effects in 2-level choice experiments. J Stat Plan Inference 2004;118:185–99.
60 Street D, Burgess L, Louviere JJ. Quick and easy choice sets: constructing optimal and nearly optimal stated choice experiments. Int J Res Mark 2005;22:459–70.
61 Sandor Z, Wedel M. Profile construction in experimental designs for mixed logit models. Market Sci 2002;21:455–75.
62 Bliemer MCJ, Rose JM. Efficient Designs for Alternative Specific Choice Experiments. Sydney: University of Sydney, 2006. Report No.: ITLS-WP-05-04.
63 Rose JM, Bliemer MCJ. Constructing Efficient Choice Experiments. Sydney: University of Sydney, 2005. Report No.: ITLS-WP-05-07.

Appendix A Example DCE question

Please compare the two screening tests below. You have decided to have a screening test, and these are the two tests you have to choose from. Which test would you choose to have?

Example	Test 1	Test 2
How many cancers the test will find	**65** out of 100	**55** out of 100
How many large polyps the test will find	**35** out of 100	**45** out of 100
The number of people who are correctly reassured by the test that they do NOT have cancer	**800** out of 1000 people	**900** out of 1000 people
The cost to you of the test	$20	$30
Dietary or medication restrictions prior to test	No	No
Collection of the stool sample	Brush stool surface gently then dab on test kit	Brush stool surface gently then dab on test kit
	(***please tick one box***)	
Which would you choose?	**Test 1** ☐	**Test 2** ☐